1 A globally calibrated scheme for generating daily meteorology from monthy statistics:Global-WGEN (GWGEN) v1.0

This paper deals with the problem of constructing a statistical weather generator for obtaining / generating daily meteorology based on monthly statistics of the following five variables, precipitation, min temperature, max temperature, cloudness and wind speed. The data used are daily entries but the model is built so that the model parameters at the daily resolution to be expressed and therefore possible to compute from monthly statistics.

GWGEN is based on the WGEN by [7] , but diverges from it by using a 2nd order Markov chain and a hybrid model with Gaussian and GP distributions for modelling the precipitation occurrence and amount respectively. The latter model has been in [4] and [6]. Here though references are missing since both these models have been studied and applied extensively to different data sets.

The problem this work deals with is an interesting one. Unfortunatelly the presentation is lacking in clarity and probabilistic rigor. Moreover the biggest limitation of the weather generator, which is also mentioned by the authors, is the absence of the spatial factor. The spatial aspect of the problem is essential since there is spatial dependence between each variable but also between the different variables and the weather at one location today moves to another nearby location tomorrow.

Some specific comments follow:

- Section 2.2.1. The first line is rather strange if one takes into account that this is actually the frequential definition of probability. The probability that a given day is wet is defined as
$$P(\text{wet}) = \frac{\#\text{ wet days}}{\#\text{ total days}},$$
for a specific month and station, so obviously there is a strong relationship. They represent exactly the same thing.

- Use of a 2nd order M-C gives better fit and results when modelling precipitation, see for example the study done in [5]. A 2nd order M-C is characterised by the transition probabilities $p_{ijk}, i, j, k = 0, 1$, therefore a total of 8 transition probabilities. I understand that the authors are interested only at the event of a wet day, i.e. we need $p_{ij1}, i, j = 0, 1$. These probabilities would be : $p_{001}, p_{101}, p_{011}, p_{111}$. Could the authors explain why instead of the last two they model p_{11}?

- In Fig.2 the fit is per station in a given month or for all months and stations together? The authors could do a better job explaining waht it is plotted in every Figure.

- In section 2.2.2, line 11: The strong relation... The mean of a gamma random variable equals the product of its two parameters. I.e $E(\Gamma) = \alpha\theta$.

- Cleary the extreme values cannot be modelled using the Gamma distribution, it is not suitable for this.

- Page 8, line 9 : I would prefer the use of the term density since distribution is usually reserved for the cumulative distribution function.

- How was the estimation of the Gamma distribution parameters performed? If the authors used likelihood, how did they deal with the fact that the the excesses above level μ are modelled as GP. [2] and [1] suggest a type of modeified likelihood that treats the excesses as sensored data.

- If α and θ are estimated by fitting the distribution to the data, then $E(\Gamma) = \bar{p} = \alpha\theta$. So what exactly is modelled by (7) and (8)? I am confused about what the authors are trying to achieve here.

- Fig. 11 Right. The data do not seem to be in a linear relation here. I think the authors shoud try some other relation or transformation also.

- Section 2.2.6. I could appreciate some comments on why the matrices A and B are needed and what they actually represent or try to model. Moreover, are the matrices estimated for each station and for every month? I assume that they are estimated using all months and stations together? How is something like this justified?

- What is the exact length of each simulation record? When we compare simulated versus observed records I assume that the simulated records are of exactly the same length as he observed ones?

- The authors notice that the gamma distribution does not perform so well for low values. Maybe it would make sense to stich another distribution for these low values, in the same fashion they did for the high ones.

- Section 2.5 The choice of the threshold μ is a rather difficult one, see for example [3]. The problem is that the fitting of the GP by likelihood, is based on the assumption that the excesses above level μ are independent and identically distributed. A rather difficult to satisfy assumption. If the level μ is chosen too low this will result to too many excesses that will be probably dependent. If it is chosen too high that would result to too few excesses to make any kind of reasonable fitting. Moreover, I think the use of a global threshold is oversimplifying.

References

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